SYSTEMS AUTONOMY

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TECHNOLOGY FOR FUTURE NASA MISSIONS

AN AIAA/OAST CONFERENCE
ON CSTI AND PATHFINDER

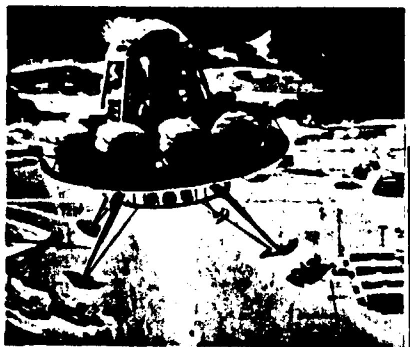
12-13 SEPTEMBER, 1988

WASHINGTON D.C.

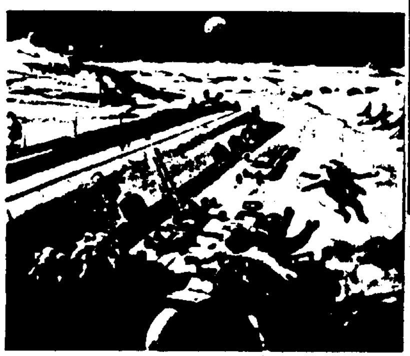
SYSTEMS AUTONOMY PROGRAM

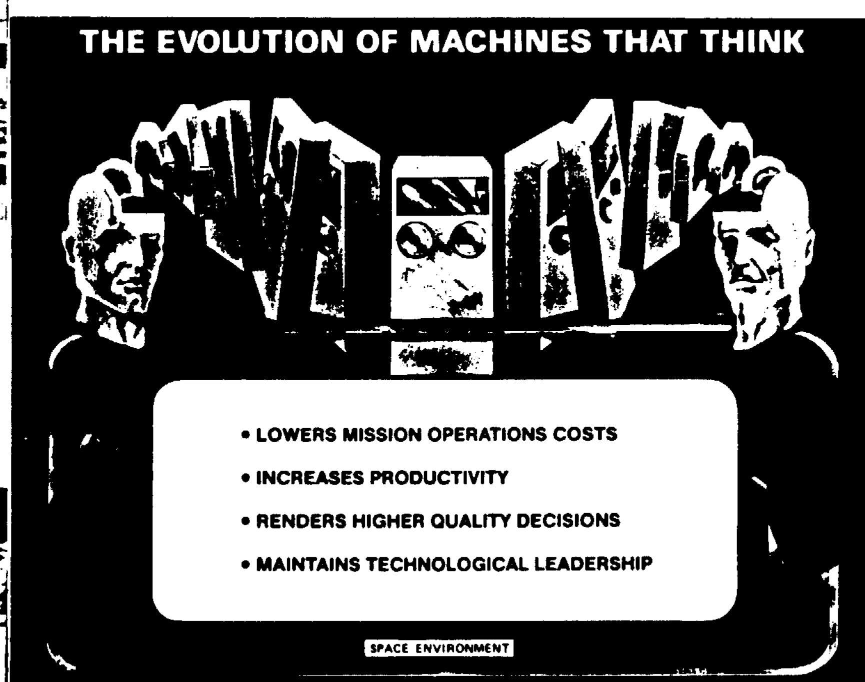
ENABLING TECHNOLOGIES FOR THE NATIONAL SPACE CHALLENGES

MARS EXPLORATION

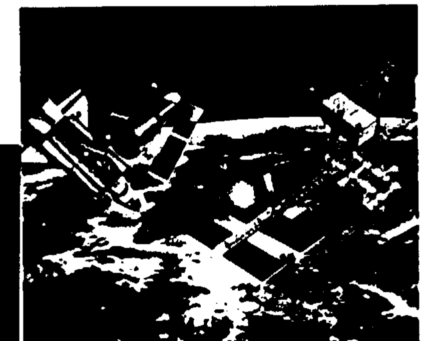


LUNAR OUTPOST

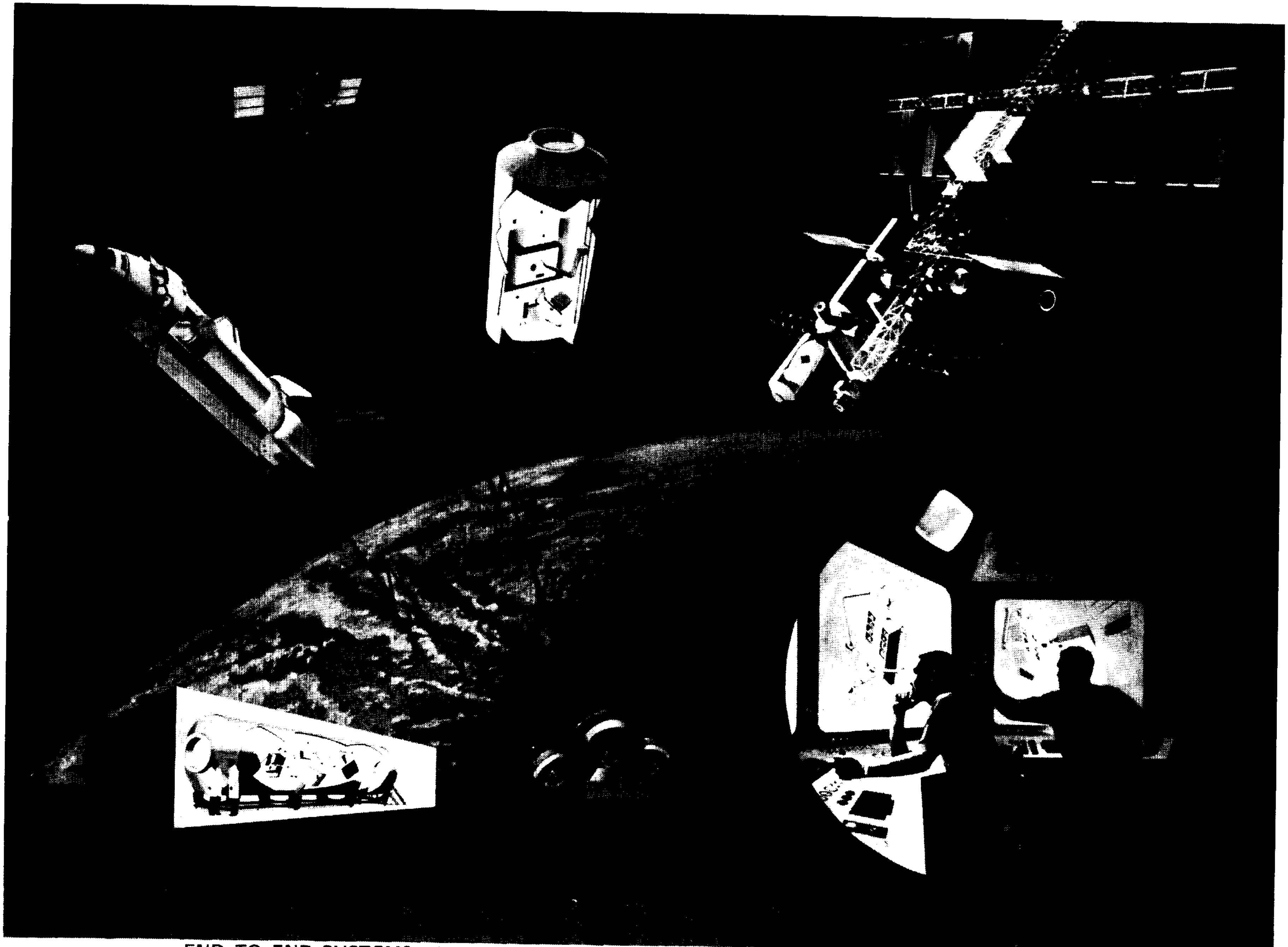




PERMANENT PRESENCE IN SPACE



TRANSPORTATION



END-TO-END SYSTEMS INTEGRATION OF HUMANS, INTELLIGENT SYSTEMS, AND FACILITIES


Humans-in-Space
Operations

SYSTEMS AUTONOMY PROGRAM

WHY INTELLIGENT AUTONOMOUS SYSTEMS

REDUCE MISSION OPERATIONS COSTS

- AUTOMATE LABOR INTENSIVE OPERATIONS

INCREASE MISSION PRODUCTIVITY

- AUTOMATE ROUTINE ONBOARD HOUSEKEEPING FUNCTIONS

INCREASE MISSION SUCCESS PROBABILITY

- AUTOMATE REAL-TIME CONTINGENCY REPLANNING

DESCRIPTION OF INTELLIGENT AUTONOMOUS SYSTEMS

CHARACTERISTICS

KNOWLEDGE-BASED SYSTEMS

- DYNAMIC WORLD KNOWLEDGE ACQUISITION, UNDERSTANDING, AND EXECUTION OF COMMAND FUNCTIONS
- RELIABLE DECISIONS IN UNCERTAIN ENVIRONMENTS
- LEARNING ABILITY
- ALLOWS "GRACEFUL" RETURN TO HUMAN CONTROL

CAPABILITIES

GOAL-DRIVEN BEHAVIOR

- COMMUNICATE AT HIGH LEVELS WITH HUMANS AND OTHER MACHINES

"COLLABORATIVE" HUMAN-MACHINE INTERACTIONS

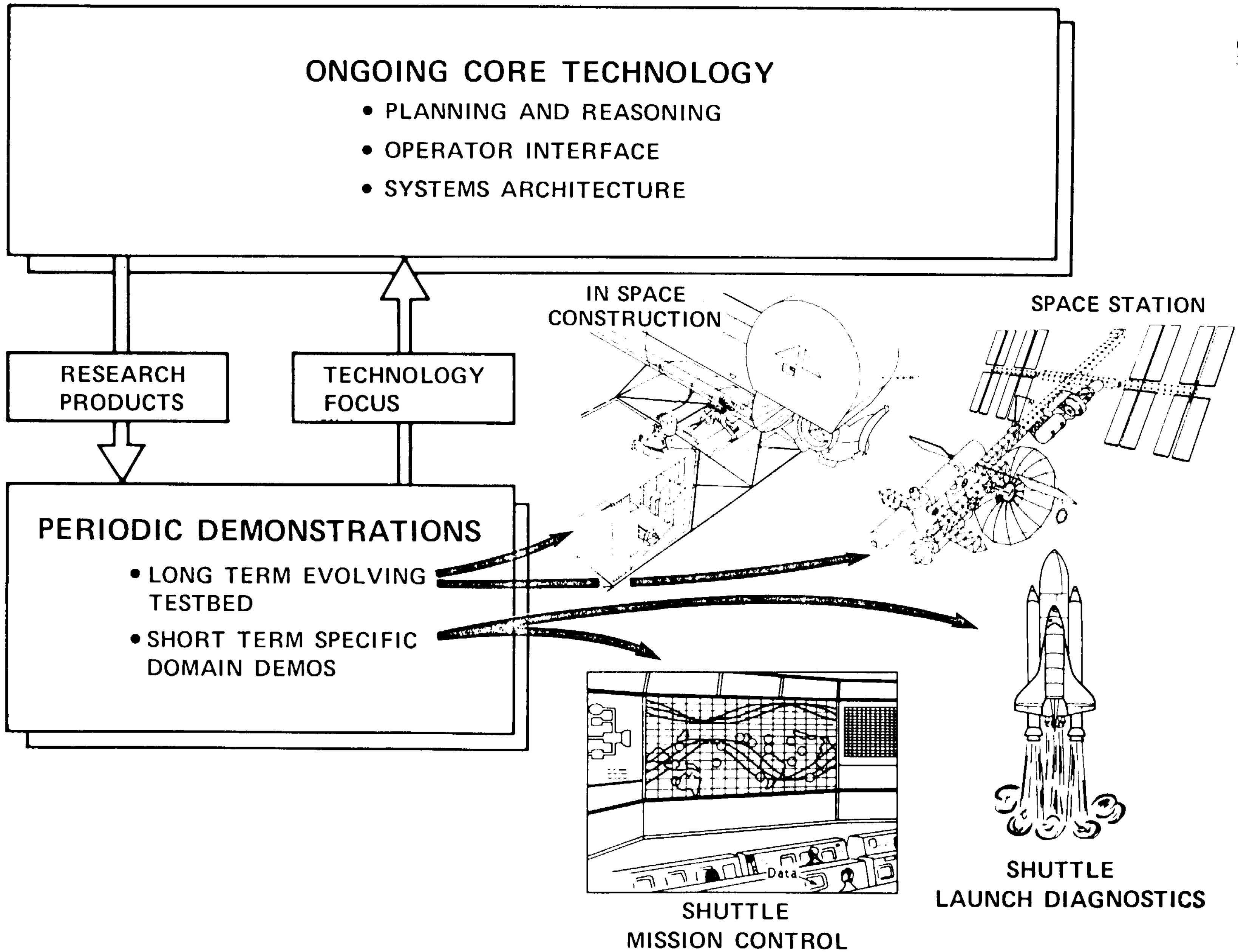
- RECOGNIZE AND RESOLVE COMMAND ERRORS

SELF-MAINTENANCE

- OPERATE AUTONOMOUSLY FOR EXTENDED PERIODS OF TIME

SYSTEMS AUTONOMY PROGRAM

HOW DO WE GET THERE - PROGRAM ELEMENTS



SYSTEMS AUTONOMY PROGRAM

TECHNICAL CHALLENGES

- REAL-TIME KNOWLEDGE-BASED SYSTEMS
- DYNAMIC KNOWLEDGE ACQUISITION AND UNDERSTANDING
- ROBUST PLANNING AND REASONING
- COOPERATING KNOWLEDGE-BASED SYSTEMS
- VALIDATION METHODOLOGIES

SYSTEMS AUTONOMY PROGRAM - TECHNOLOGICAL CHALLENGES

A. WHERE WE ARE TODAY

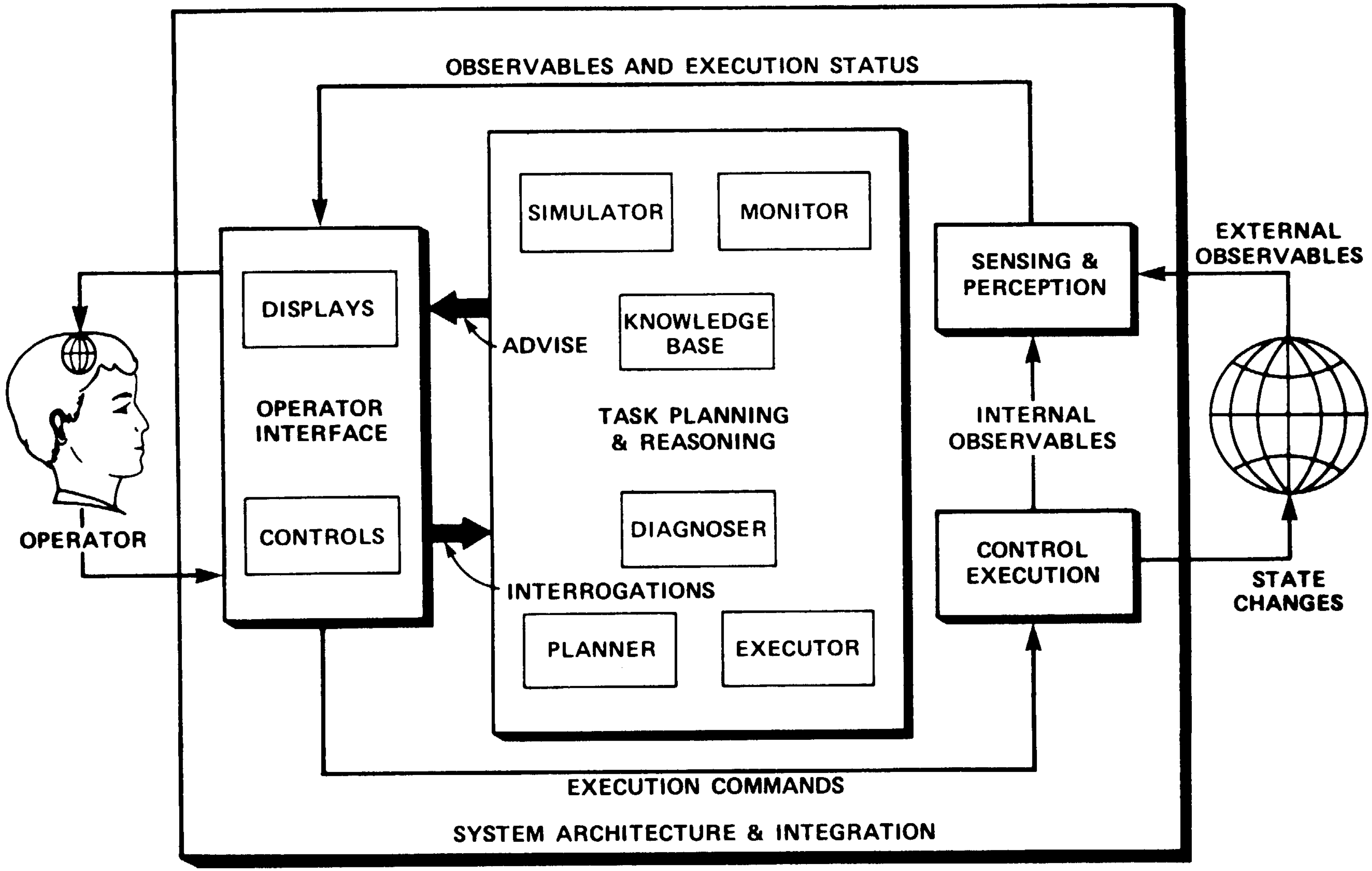
REAL-TIME KNOWLEDGE-BASED SYSTEMS
- NO PARALLEL SYMBOLIC-NUMERIC PROCESSORS
- SLOW SPECIAL-PURPOSE HARDWARE (1 GBYTE MEM, 5 MIPS)
- PROTOTYPING S/W SHELLS (ART, KEE, KNOWLEDGECRAFT)
- DIAGNOSIS AND PLANNING DECISIONS IN 1-10 MINUTES

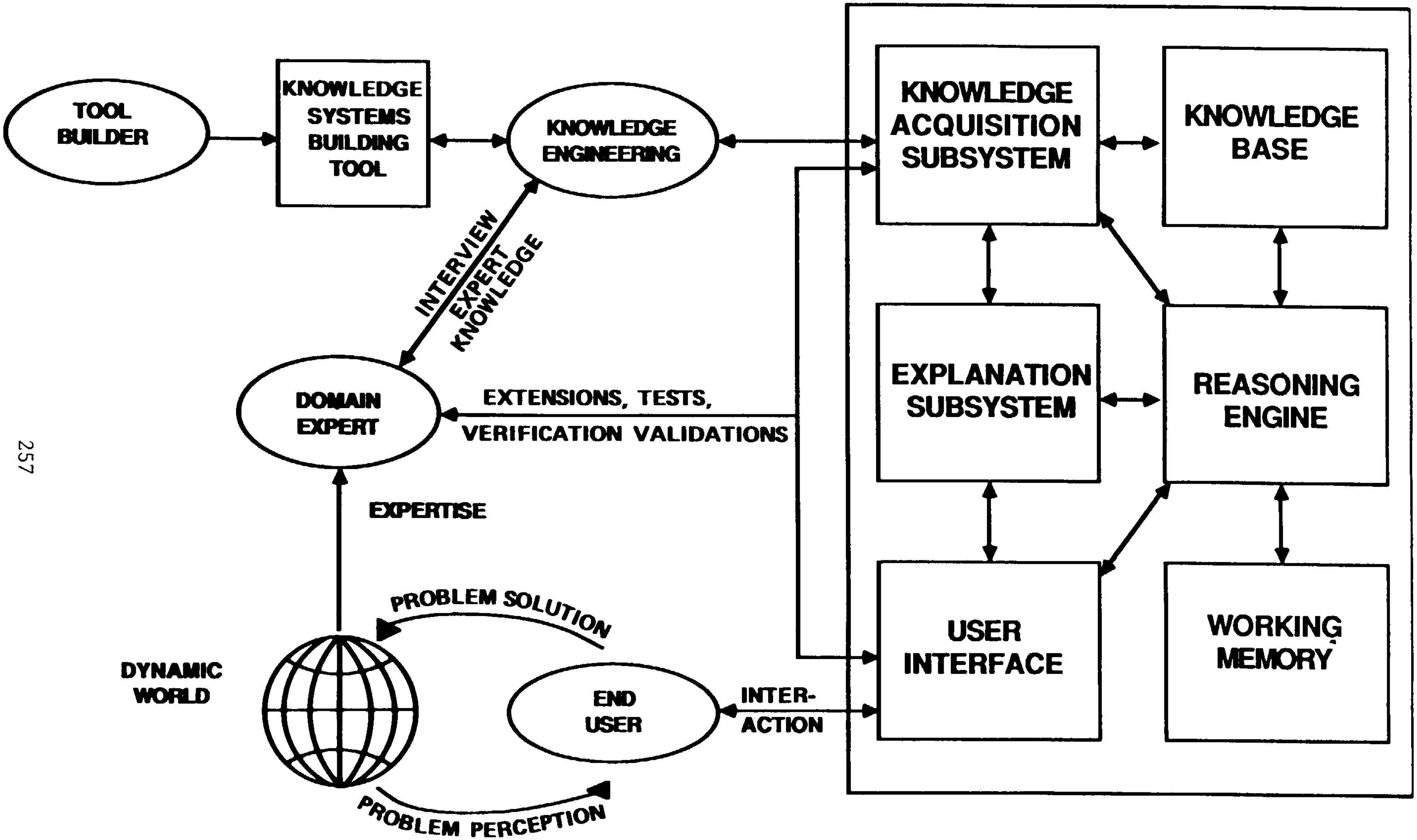
DYNAMIC KNOWLEDGE-ACQUISITION & UNDERSTANDING
- NO AUTOMATED EXPANSION OF K-B
- SMALL STATIC PRE-PROGRAMMED K-B
- DEC "XCON" LARGEST (5000 RULES, 2000 COMPONENTS)

ROBUST PLANNING AND REASONING
- HEURISTIC RULES ONLY, NO CAUSAL MODELS
- PRE-MISSION PLANNING (NO REAL-TIME REPLANNING)
- DIAGNOSIS OF ONLY ANTICIPATED SINGLE FAULTS
- "FRAGILE" NARROW DOMAINS (RAPID BREAKDOWN AT K-B LIMITS)

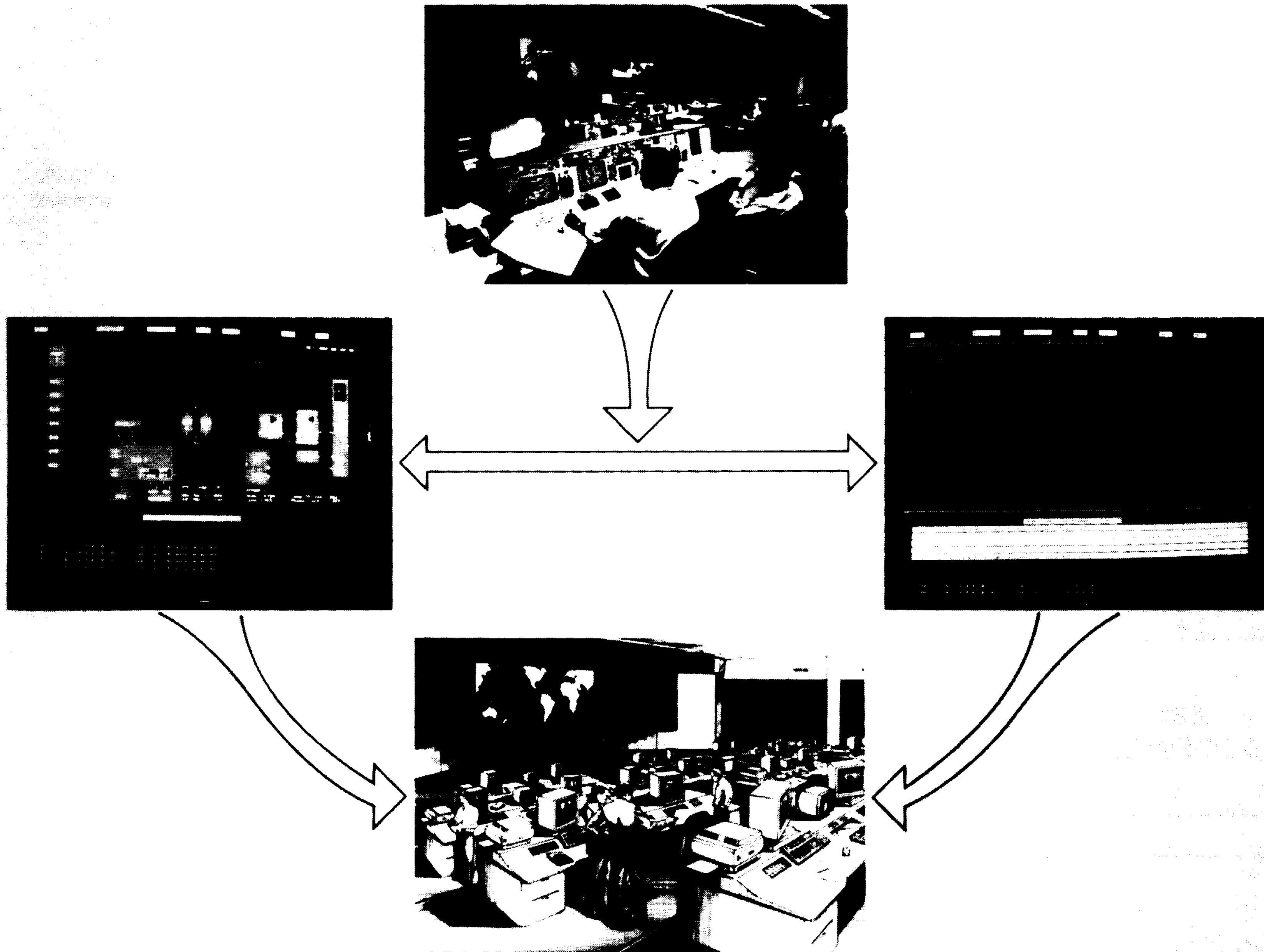
COOPERATING KNOWLEDGE-BASED SYSTEMS
- SINGLE STANDALONE DOMAIN SPECIFIC SYSTEMS
- HUMAN INTERACTION ONLY, NO INTELLIGENT SYSTEMS INTERACTION

VALIDATION METHODOLOGIES
- CONVENTIONAL TECHNIQUES FOR ALGORITHMIC SYSTEMS


OBSERVABLES AND EXECUTION STATUS
SIMULATOR
MONITOR
DISPLAYS
ADVISE
KNOWLEDGE BASE
SENSING & PERCEPTION
EXTERNAL OBSERVABLES
OPERATOR INTERFACE
TASK PLANNING & REASONING
INTERNAL OBSERVABLES
CONTROLS
DIAGNOSER
OPERATOR
INTERROGATIONS
CONTROL EXECUTION
STATE CHANGES
PLANNER
EXECUTOR
EXECUTION COMMANDS
SYSTEM ARCHITECTURE & INTEGRATION


TOOL BUILDER
KNOWLEDGE SYSTEMS BUILDING TOOL
KNOWLEDGE ENGINEERING
INTERVIEW
EXPERT KNOWLEDGE
DOMAIN EXPERT
EXTENSIONS, TESTS,
VERIFICATION VALIDATIONS
EXPERTISE
PROBLEM SOLUTION
DYNAMIC WORLD
END USER
INTER-
ACTION
PROBLEM PERCEPTION
KNOWLEDGE ACQUISITION SUBSYSTEM
KNOWLEDGE BASE
EXPLANATION SUBSYSTEM
REASONING ENGINE
USER INTERFACE
WORKING MEMORY

AUTOMATED SYSTEMS FOR IN-FLIGHT MISSION OPERATIONS
EVOLUTION OF AUTOMATION TECHNOLOGY



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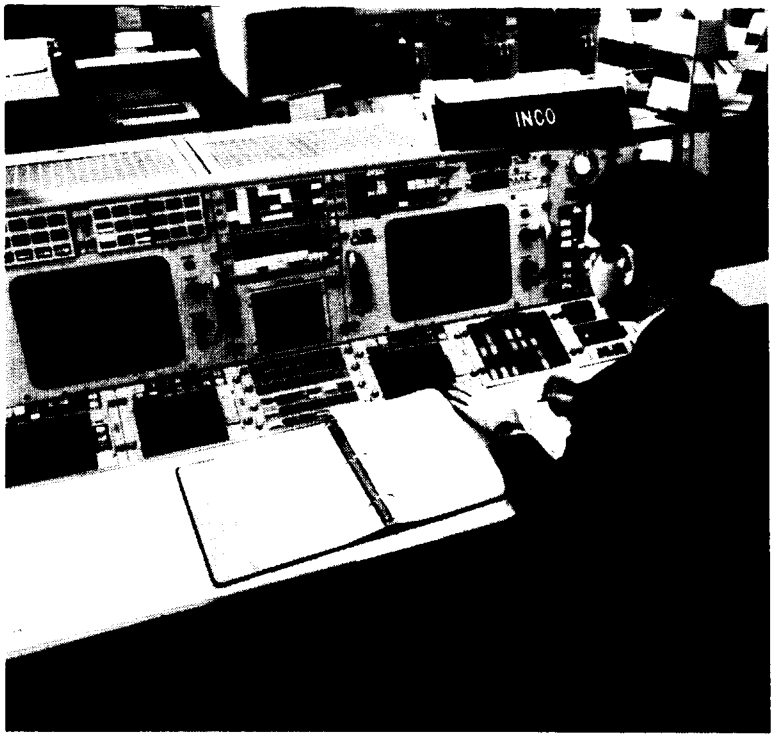


BEFORE

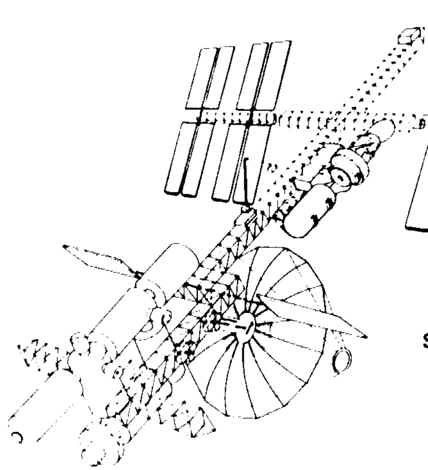
E/S

TECHNOLOGY

NOW

SYSTEMS AUTONOMY PROGRAM DEMONSTRATION

SYSTEMS AUTONOMY DEMONSTRATION PROJECT (SADP)



SPACE STATION AUTOMATION

OBJECTIVES

DEMONSTRATE TECHNOLOGY FEASIBILITY OF INTELLIGENT AUTONOMOUS SYSTEMS FOR SPACE STATION THROUGH TESTBED DEMONSTRATIONS

- 1988: SINGLE SUBSYSTEM (THERMAL)
- 1990: TWO COOPERATING SUBSYSTEMS (THERMAL/POWER)
- 1993: HIERARCHICAL CONTROL OF SEVERAL SUBSYSTEMS
- 1996: DISTRIBUTED CONTROL OF MULTIPLE SUBSYSTEMS

PARTICIPANTS AND FACILITIES

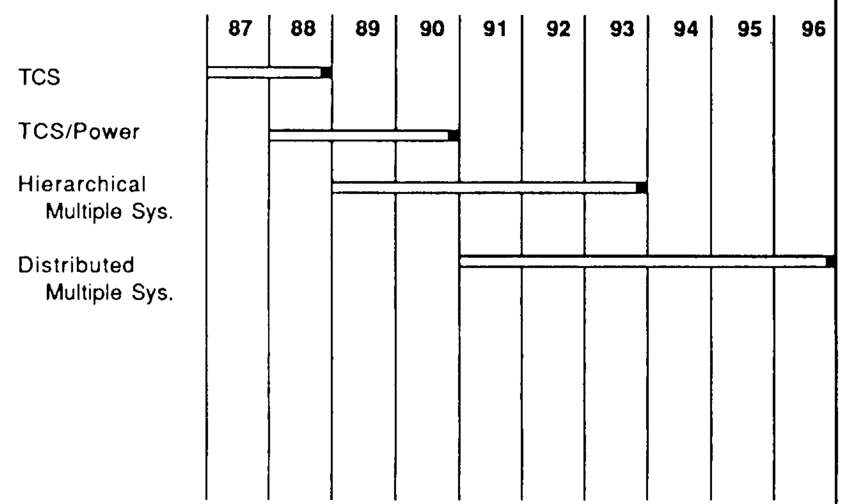
PARTICIPANTS

- AMES RESEARCH CENTER
- JOHNSON SPACE CENTER
- LEWIS RESEARCH CENTER
- MARSHALL SPACE FLIGHT CENTER
- INDUSTRY

FACILITIES

- ARC INTELLIGENT SYSTEMS LABORATORY
- JSC INTELLIGENT SYSTEMS LABORATORY
- JSC THERMAL TEST BED
- LeRC POWER TEST BED

SCHEDULE



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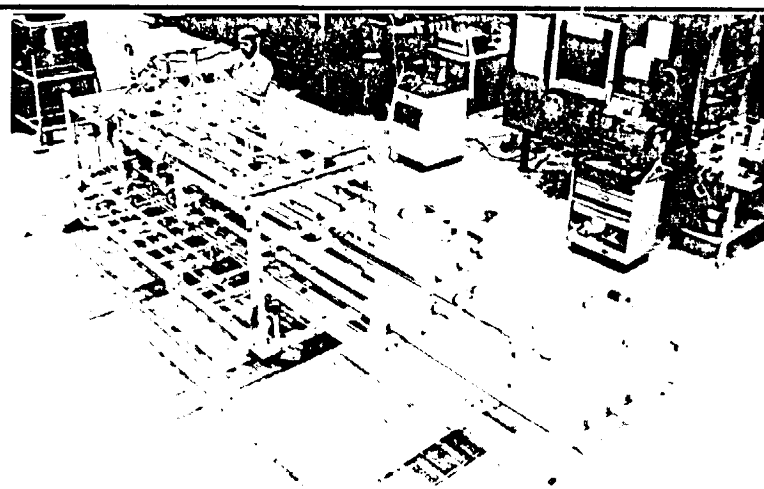
1988 DEMONSTRATION
SYSTEMS AUTONOMY DEMONSTRATION PROJECT
SPACE STATION THERMAL CONTROL SYSTEM (TEXSYS)



OBJECTIVES

IMPLEMENTATION OF AI TECHNOLOGY INTO THE REAL-TIME DYNAMIC ENVIRONMENT OF A COMPLEX ELECTRICAL-MECHANICAL SPACE STATION SYSTEM - THE THERMAL CONTROL SYSTEM.

- **REAL-TIME CONTROL**
- **FAULT DIAGNOSIS AND CORRECTION**
- **TREND ANALYSIS FOR INCIPIENT FAILURE PREVENTION**
- **INTELLIGENT HUMAN INTERFACE**
- **CAUSAL MODELLING**
- **VALIDATION TECHNIQUES**

PARTICIPANTS AND FACILITIES

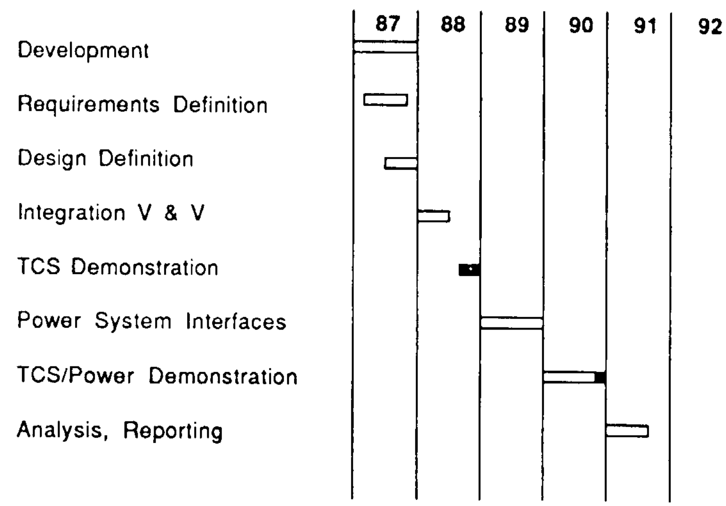
PARTICIPANTS

- AMES RESEARCH CENTER
- JOHNSON SPACE CENTER
- INDUSTRY: LEMSCO, ROCKWELL INTERNATIONAL, GEOCONTROL SYSTEMS, STERLING SOFTWARE

FACILITIES

- ARC INTELLIGENT SYSTEMS LABORATORY
- JSC INTELLIGENT SYSTEMS LABORATORY
- JSC THERMAL TEST BED

SCHEDULE



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SYSTEM AUTONOMY DEMONSTRATION PROJECT

TCS FUNCTIONAL CAPABILITIES

PROTOTYPE OBJECTIVES	DEMO 1/87
CAUSAL MODELS/SIMULATION	●
LIMITED FAULT DIAGNOSIS	●

KNOWLEDGE BASE EXPANSION

DEMONSTRATION OBJECTIVES	1 6/87	2 9/87	3 12/87	4 2/88	5 5/88
NOMINAL REAL-TIME CONTROL	◍	◍	◍	●	●
FAULT DIAGNOSIS AND CORRECTION	◍	◍	◍	●	●
TREND ANALYSIS	○	◍	◍	◍	●
INTELLIGENT INTERFACE	○	○	◍	◍	●
DESIGN ASSISTANCE	○	○	○	◍	●
TRAINING ASSISTANCE	○	○	○	◍	●

SYSTEMS AUTONOMY PROGRAM - TECHNOLOGICAL CHALLENGES

B. WHERE WE NEED TO GO

REAL-TIME KNOWLEDGE-BASED SYSTEMS
- PARALLEL SYMBOLIC-NUMERIC PROCESSORS (100 GBYTES, 500 MIPS)
- NEURAL NETWORKS (BRAIN CELL EMULATION)
- LAYERED TRANSPARENT SW
- DIAGNOSIS AND PLANNING IN MILLISECONDS

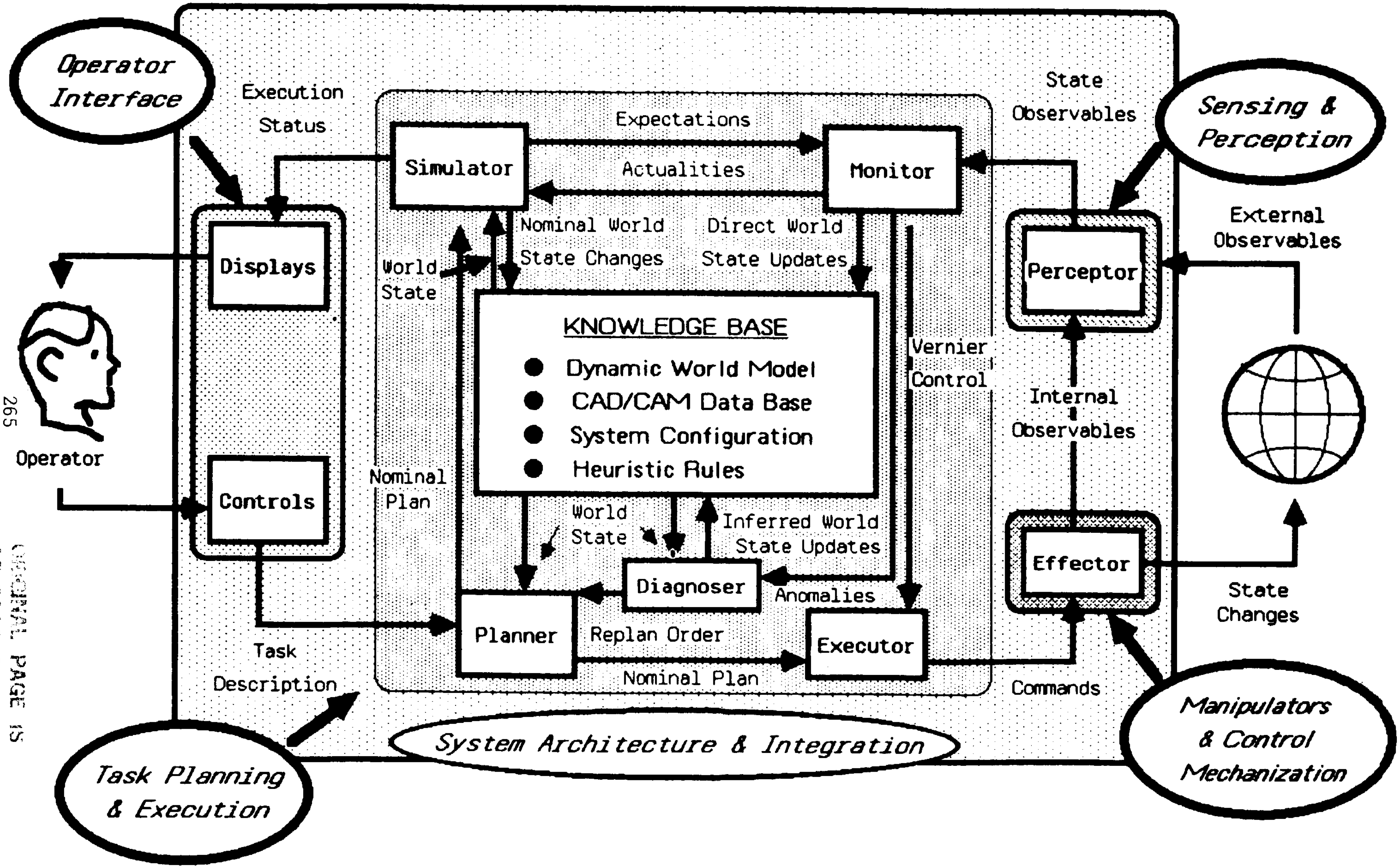
DYNAMIC KNOWLEDGE ACQUISITION & UNDERSTANDING
- AUTOMATED K-B EXPANSION IN REAL-TIME (LEARNING)
- LARGE DYNAMIC DISTRIBUTED K-B

ROBUST PLANNING AND REASONING
- COMBINED HEURISTIC RULES AND CAUSAL MODELS
- REAL-TIME CONTINGENCY REPLANNING
- DIAGNOSIS OF UNANTICIPATED FAULTS
- SPECIFIC DOMAINS ON BROAD GENERIC K-B (GRACEFUL DEGRADATION)

COOPERATING KNOWLEDGE-BASED SYSTEMS
- HIERARCHICAL AND DISTRIBUTED SYSTEMS
- HUMAN AND INTELLIGENT SYSTEMS INTERACTION

VALIDATION METHODOLOGIES
- METHODOLOGY FOR EVALUATING DECISION QUALITY
- FORMAL THEORETICAL FOUNDATION

Architecture of an Autonomous Intelligent System

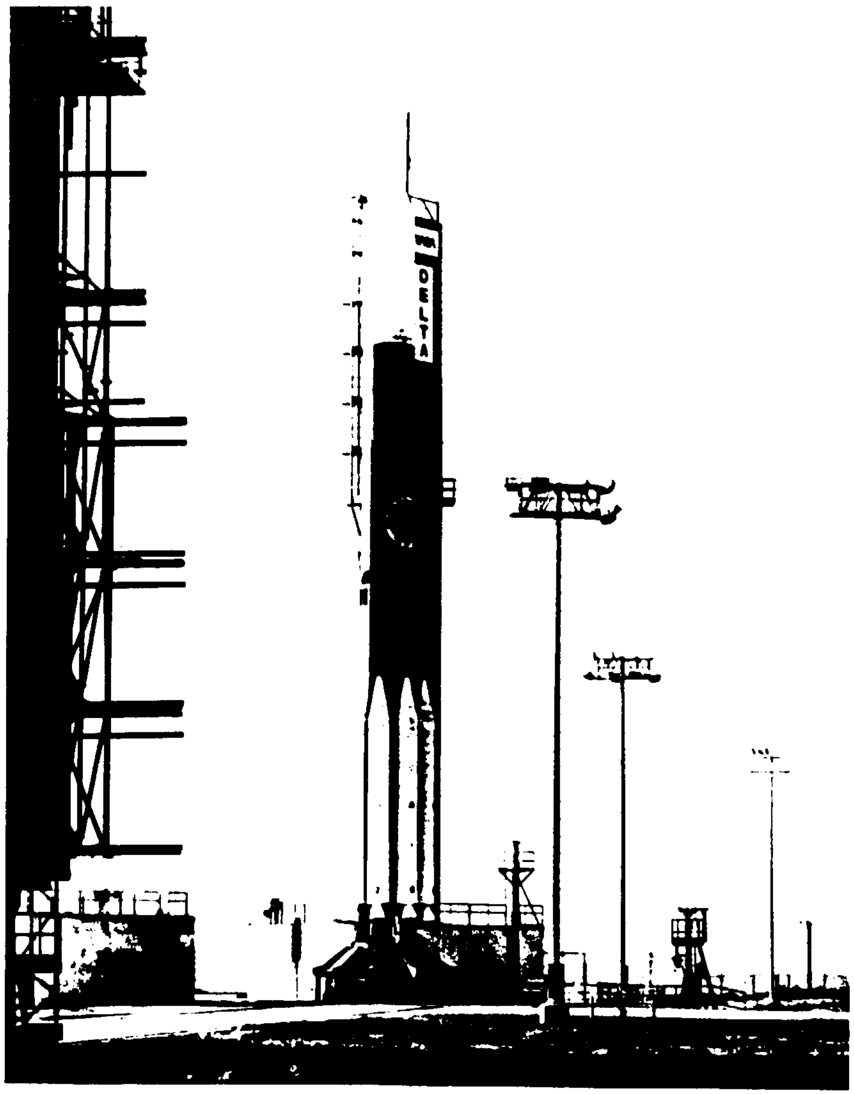


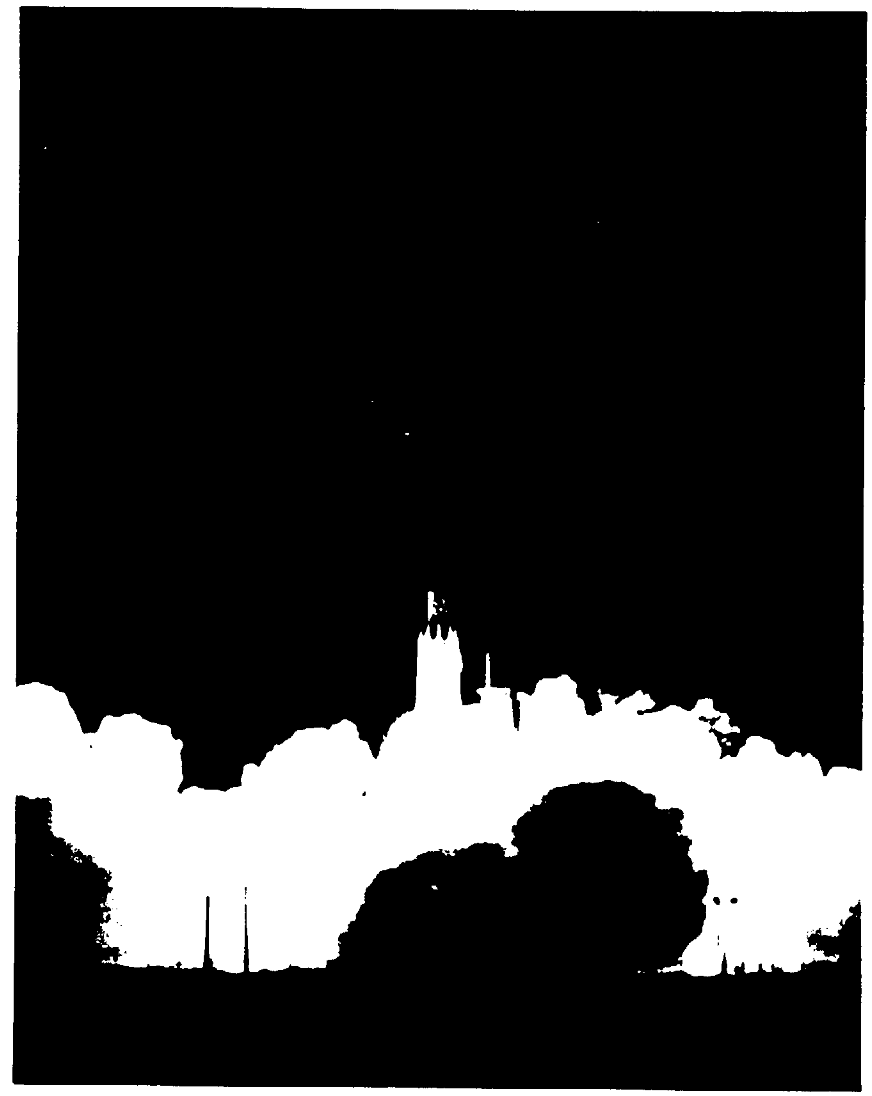
SYSTEMS AUTONOMY DEMONSTRATION PROJECT

Technology Demonstration - Evolutionary Sequence

1988 **Automated Control Of Single Subsystem ("Intelligent Aide")** **Thermal Control System** * Monitor/real-time control of a single subsystem * Goal and causal explanation displays * Rule-based simulation * Fault recognition/warning/limited diagnosis * Resource management * Reasoning assuming standard procedures	**1990** **Automated Control of Multiple Subsystems ("Intelligent Apprentice")** **Thermal Control System and Power System** * Coordinated control of multiple subsystems * Operator aids for unanticipated failures * Model-based simulation * Fault diagnosis for anticipated failures * Real-time planning/replanning * Reasoning about nonstandard procedures
1993 **Hierarchical Control of Multiple Subsystems ("Intelligent Assistant")** * Multiple subsystem control: ground and space * Task-oriented dialogue & human error tolerance * Fault recovery from unanticipated failures * Planning under uncertainty * Reasoning about emergency procedures	**1996** **Distributed Control Of Multiple Subsystems ("Intelligent Associate")** * Autonomous cooperative controllers * Goal-driven natural language interface * Fault prediction and trend analysis * Automated real-time planning/replanning * Reasoning/learning, supervision of on-board systems

AUTONOMOUS SYSTEMS FOR ADVANCED LAUNCH SYSTEMS (ALS)
UNMANNED LAUNCH VEHICLES





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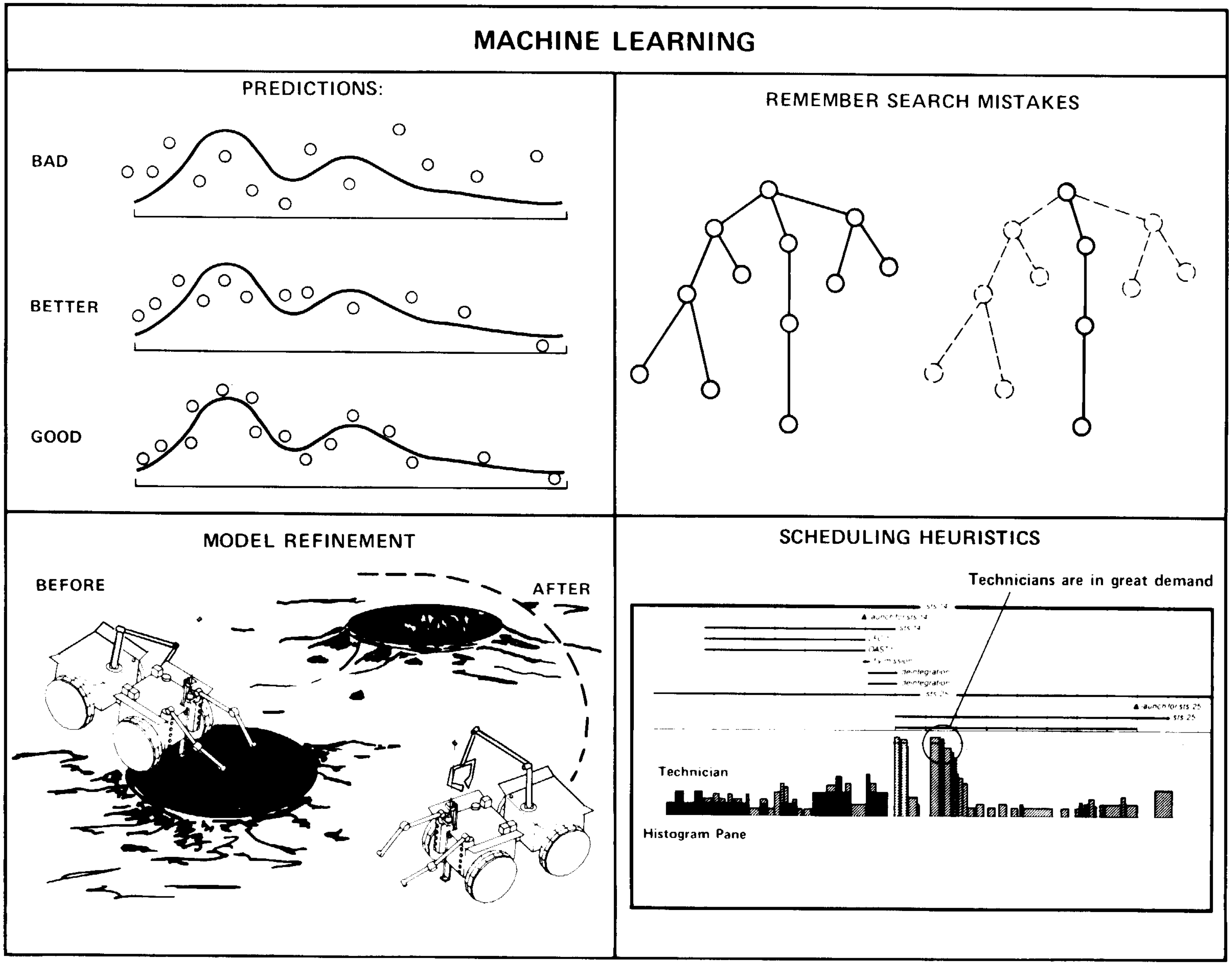
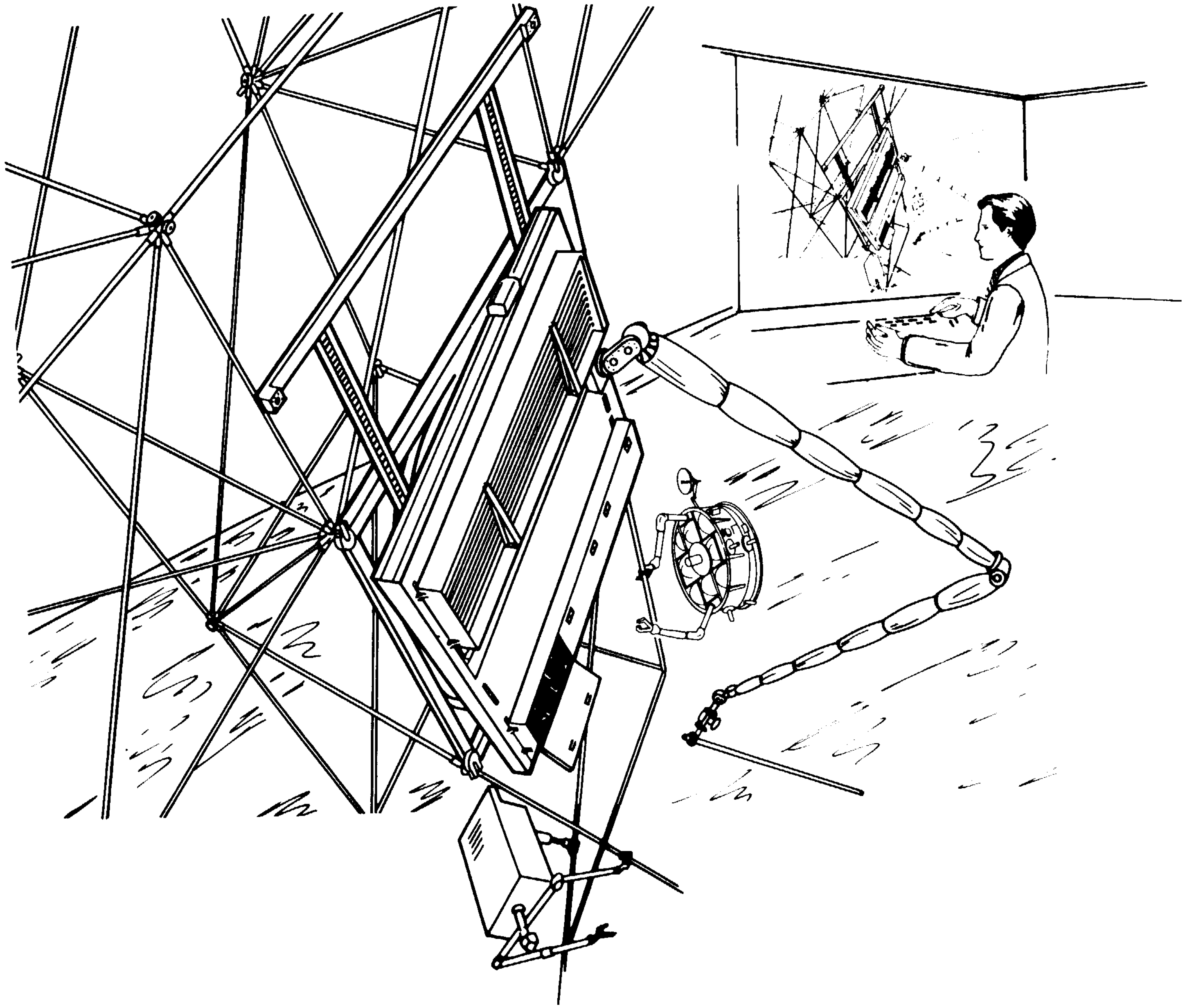
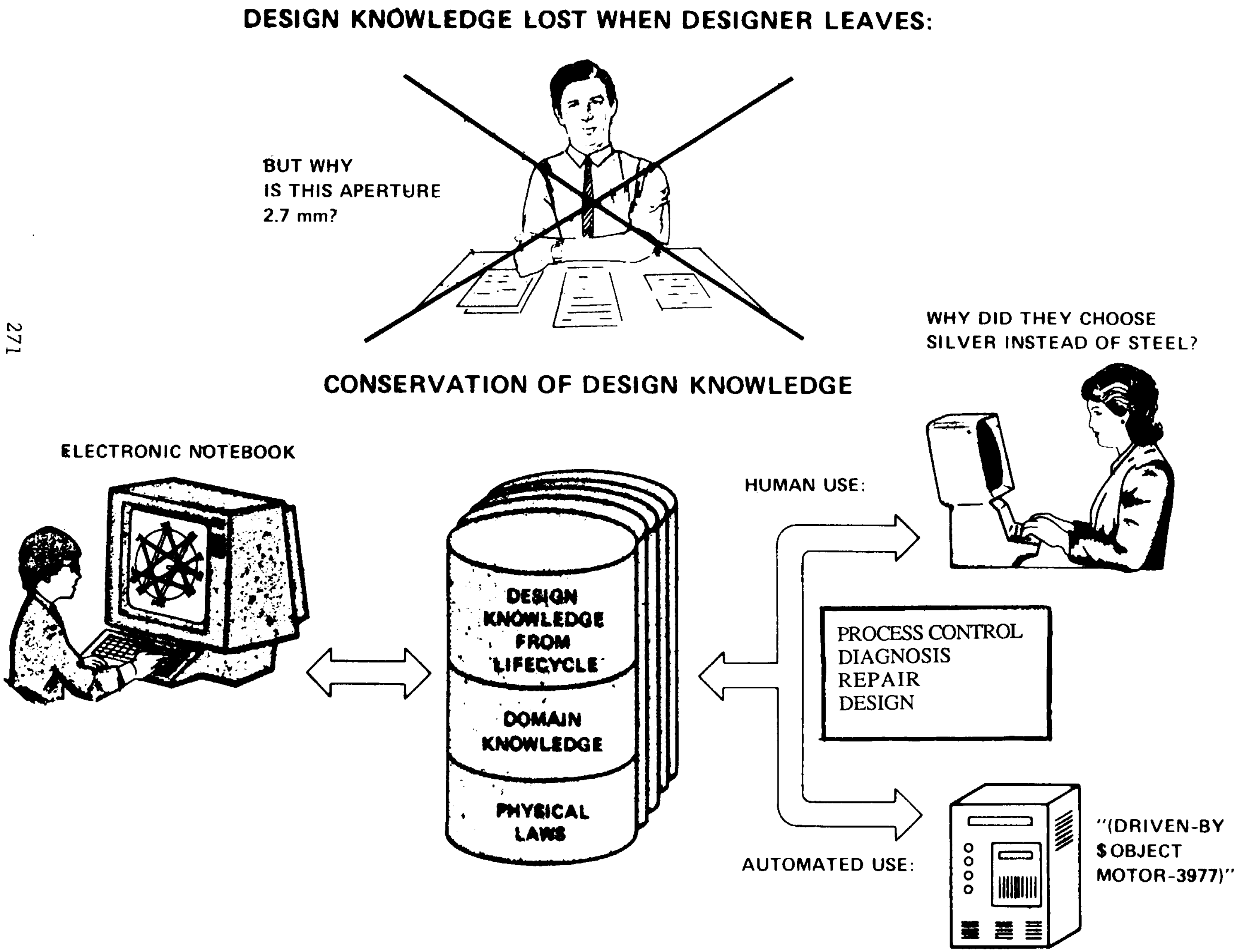
AI Research Issues

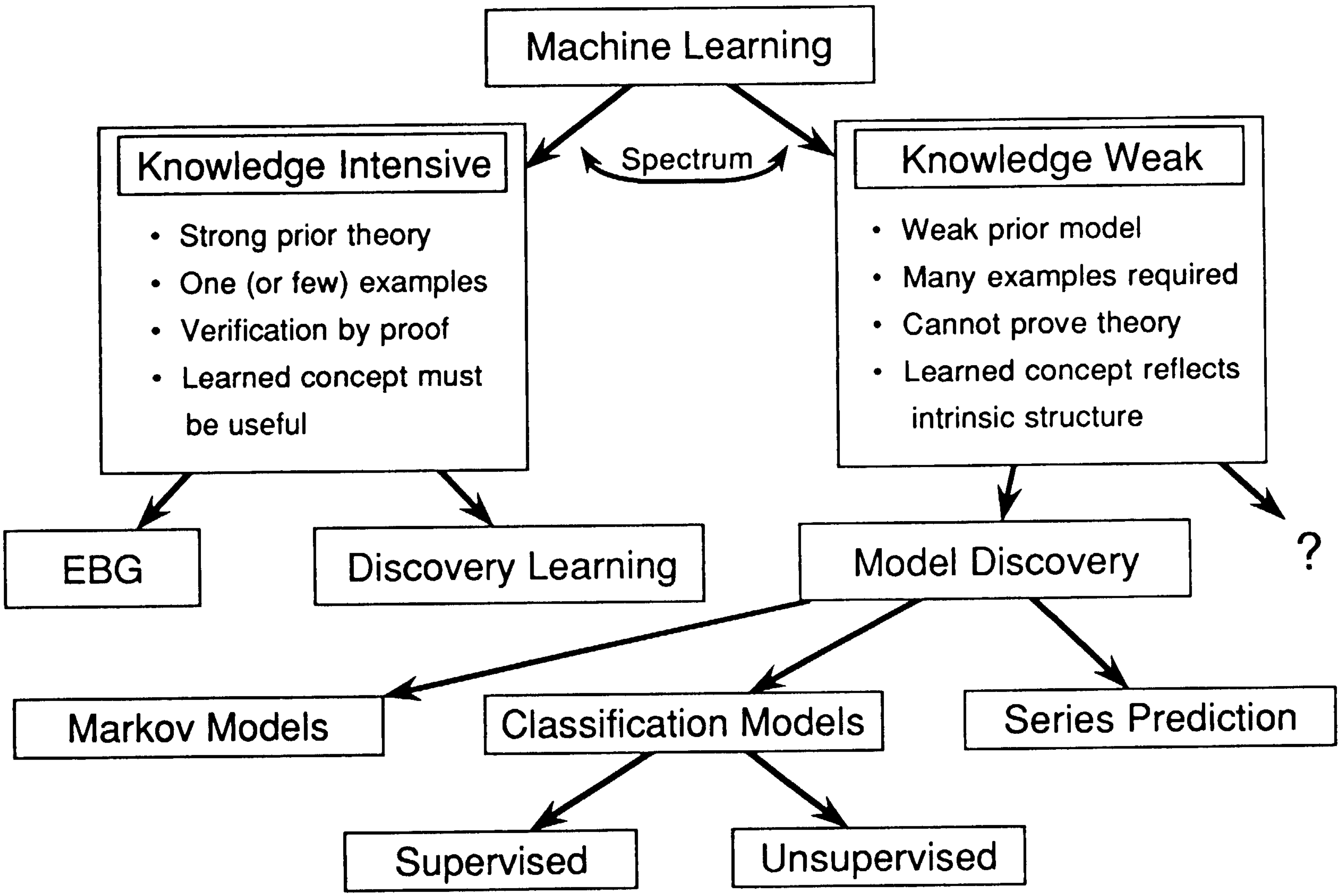
- MACHINE LEARNING
- COOPERATING KNOWLEDGE-BASED SYSTEMS
- REAL-TIME ADVANCED PLANNING AND SCHEDULING METHODOLOGIES
- MANAGEMENT OF UNCERTAINTY
- AUTOMATED DESIGN KNOWLEDGE CAPTURE
- VALIDATION OF KNOWLEDE-BASED SYSTEMS

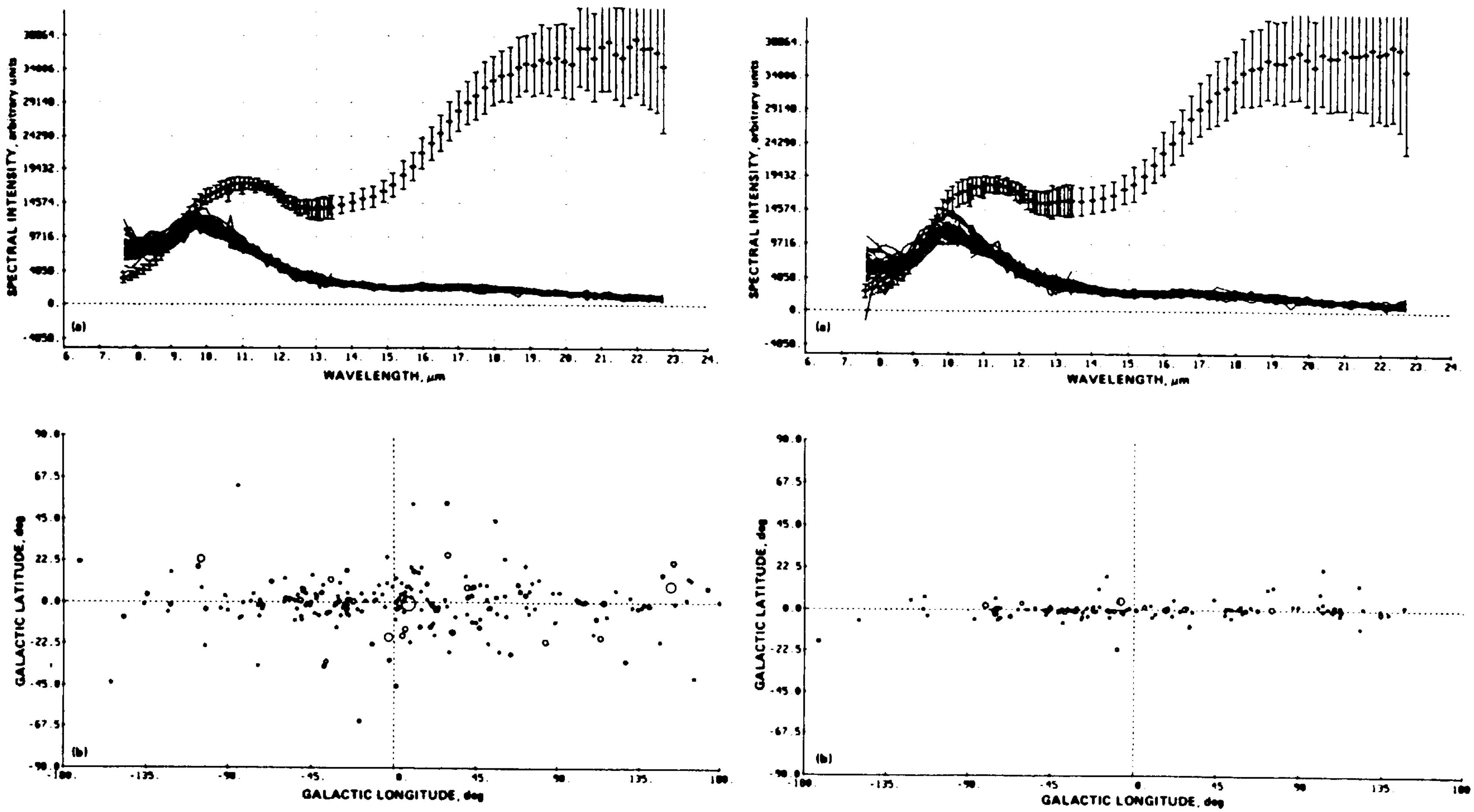

MACHINE LEARNING
PREDICTIONS:
BAD
BETTER
GOOD
REMEMBER SEARCH MISTAKES
MODEL REFINEMENT
BEFORE
AFTER
SCHEDULING HEURISTICS
Technicians are in great demand
Technician
Histogram Pane

COOPERATIVE INTELLIGENT SYSTEMS




DESIGN KNOWLEDGE LOST WHEN DESIGNER LEAVES:
BUT WHY
IS THIS APERTURE
2.7 mm?
WHY DID THEY CHOOSE
SILVER INSTEAD OF STEEL?
CONSERVATION OF DESIGN KNOWLEDGE
ELECTRONIC NOTEBOOK
DESIGN
KNOWLEDGE
FROM
LIFECYCLE
DOMAIN
KNOWLEDGE
PHYSICAL
LAWS
HUMAN USE:
PROCESS CONTROL
DIAGNOSIS
REPAIR
DESIGN
AUTOMATED USE:
"(DRIVEN-BY
$OBJECT
MOTOR-3977)"

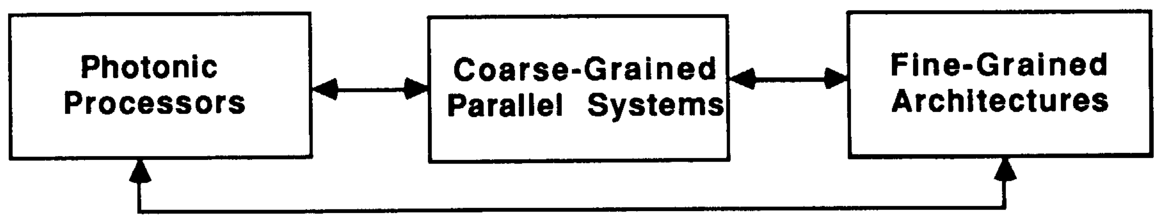

Machine Learning
Spectrum
Knowledge Intensive
• Strong prior theory
• One (or few) examples
• Verification by proof
• Learned concept must be useful
Knowledge Weak
• Weak prior model
• Many examples required
• Cannot prove theory
• Learned concept reflects intrinsic structure
EBG
Discovery Learning
Model Discovery
?
Markov Models
Classification Models
Series Prediction
Supervised
Unsupervised



The spectra show two closely related IRAS classes with peaks at 9.7 and 10.0 microns. This discrimination was achieved by considering all channels of each spectrum. AutoClass currently has no model of spectral continuity. The same results would be found if the channels were randomly reordered.

The galactic location data, not used in the classification, tends to confirm that the classification represents real differences in the sources.

Evolution of Advanced Architectures for Real-time, On-board Teraflop Systems



	Photonic Processors	Coarse-Grained Parallel Systems	Fine-Grained Architectures
Function	RT Image Processing	Knowledge Under-standing & Control	Deep Reasoning
Technology Status	Applied R&D	Development	Basic Research
Technology Forecast	Late 1990s	Current	Early 2000s
Examples	KBS-controlled Photonic Processor	SVMS (6-Processor System)	Neural Networks Fuzzy Logic Computes and Controllers

Computer Architecture Research Issues (Numeric/Symbolic Multiprocessor Systems)

- OPERATING SYSTEMS FOR REAL-TIME MULTIPROCESSING SYSTEMS IN A HETEROGENEOUS ENVIRONMENT
- VALIDATED COMPILERS AND TRANSLATORS FOR AN ADA-BASED MULTIPROCESSING ENVIRONMENT
- DATABASE MANAGEMENT FOR LARGE DISTRIBUTED DATABASES GREATER THAN 10GB
- AUTOMATED LOAD SCHEDULING FOR MULTIPROCESSORS
- REAL-TIME FAULT TOLERANCE AND RECONFIGURATION
- RADIATION HARDNESS WITH MINIMUM PERFORMANCE COMPROMISES
  - PROCESS TECHNOLOGY
  - VLSI/VHSIC TRADEOFFS
  - EFFICIENT COMPILERS AND INSTRUCTION SET ARCHITECTURES

SPACEBORNE VHSIC MULTIPROCESSOR SYSTEM (SVMS)
NASA/AF/DARPA COLLABORATION

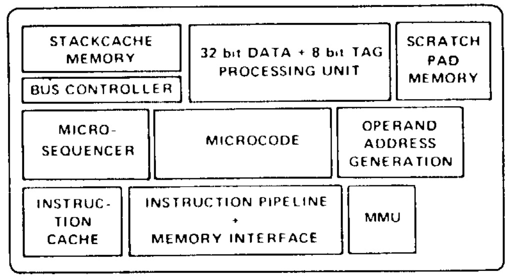
PROCESS

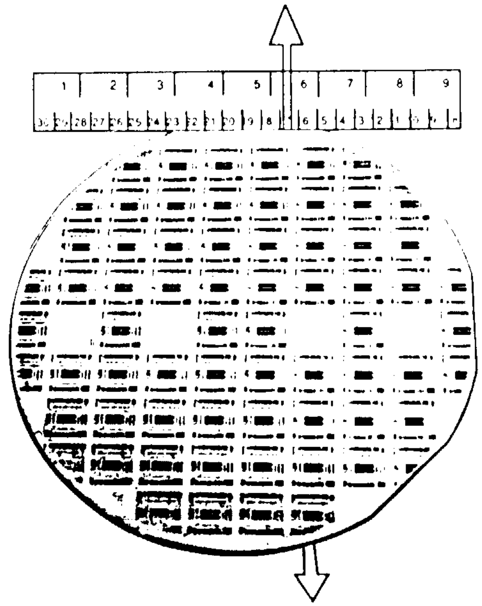
VHSIC TECHNOLOGY

- 0.5μ TARGET
- 1.25μ BACKUP

RAD-HARD CMOS

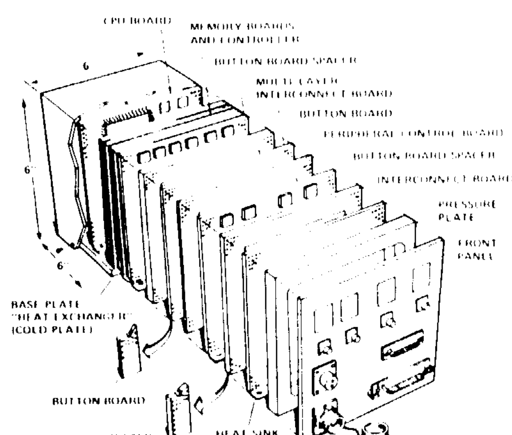
- 10^5 RADS RADIATION RESISTANCE
- NO SINGLE EVENT UPSETS



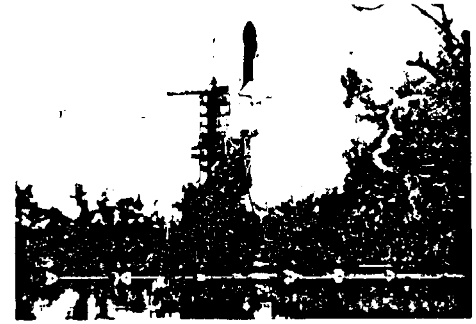


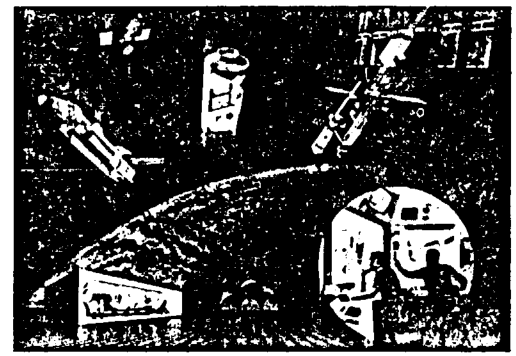
SYSTEM CHARACTERISTICS

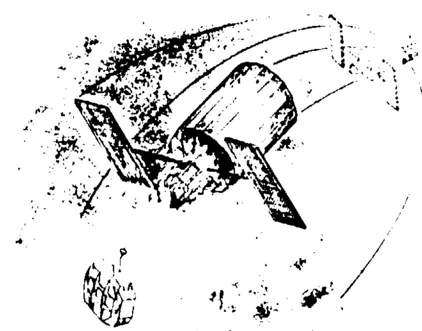
- PARALLEL ARCHITECTURE
  - 40-BIT SYMBOLIC PROCESSORS
  - 32-BIT NUMERIC PROCESSORS
- FAULT-TOLERANCE/AUTOMATED RECONFIGURATION
- OPTICAL INTERCONNECTS
- 25 MIPS SUSTAINED UNIPROCESSOR PERFORMANCE (40 MIPS TARGET)
  - MINIMUM OF 100 MIPS OVERALL SYSTEM PERFORMANCE
- DBMS FOR 10G BYTE MEMORY MANAGEMENT

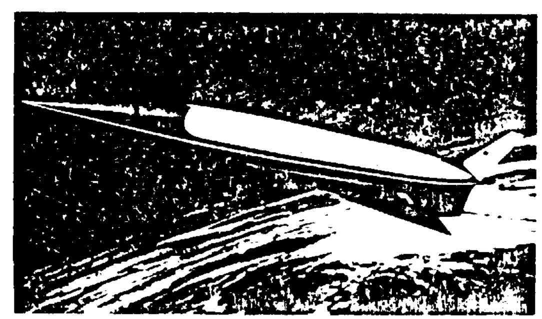


POTENTIAL SPACE
&
AERONAUTICS APPLICATIONS









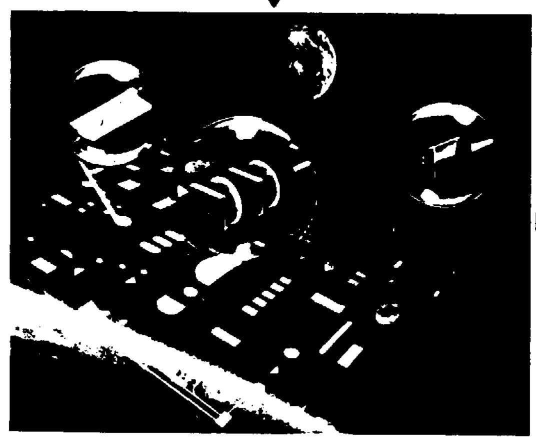
PHOTONIC PROCESSOR FOR REAL-TIME IMAGE UNDERSTANDING

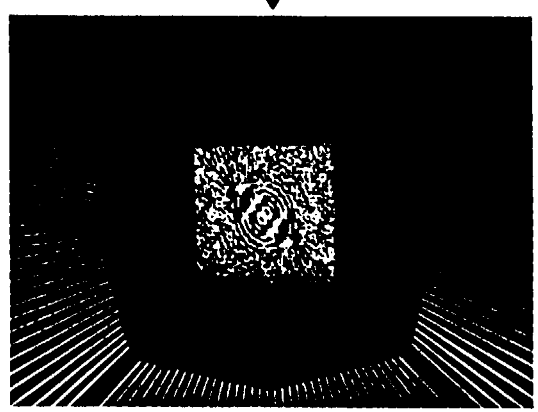
OBJECTIVES

- **REAL-TIME PHOTONIC PROCESSORS & TECHNIQUES**
  for Terrain Analysis Tasks
- **SYSTEM CONTROL & INTEGRATION OF EMBEDDED PHOTONIC PROCESSORS**
  with Integrated Numeric/Symbolic Multiprocessor Systems
- **TECHNOLOGY FEASIBILITY DEMONSTRATIONS**
  Focused on Planetary Rovers & Space Vehicles

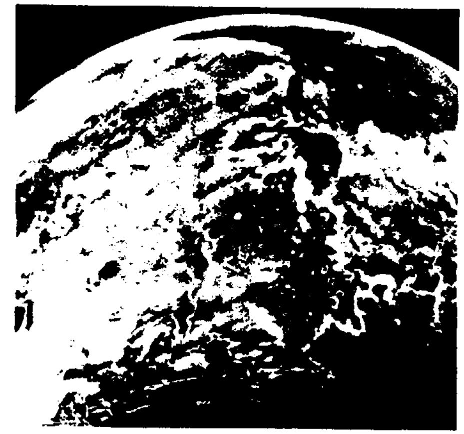
BENEFITS

- Real-time, High Performance Parallel Processing for Image Processing & Understanding
- Fault Tolerance
- Low Power, Weight, and Size





POTENTIAL APPLICATIONS



Autonomous Landing

Sample Acquisition and Analysis

Sample Return

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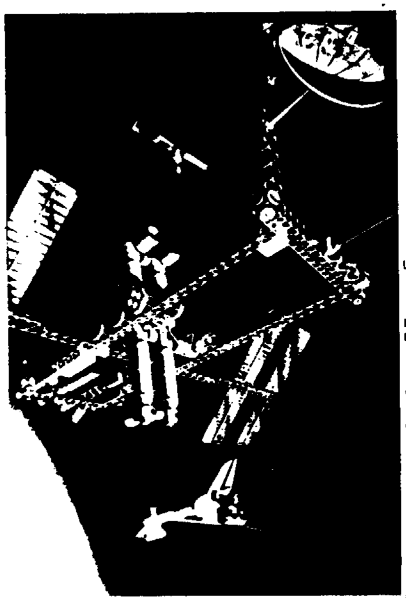
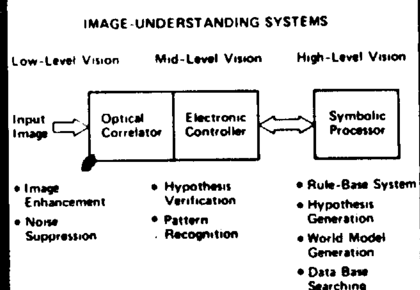




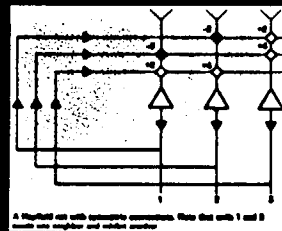
Knowledge-Based Systems

The tasks involved with an image-understanding-system can be divided into three layers as shown. The problem is to find a synergistic balance between all layers so that as knowledge of the image accrues, the reliability of the interpretation, recognition, and enhancement increases, while the amount of required computation decreases. Methodologies of organizing a knowledge-base of object and using a rule-based system to effectively search the knowledge-base and directing the computations of photonic processors are being developed. The majority of the domain specific knowledge for a task will reside in the interpretative level making the photonic processor a general purpose computing tool.

Neural Networks

NASA
Ames Research
Center

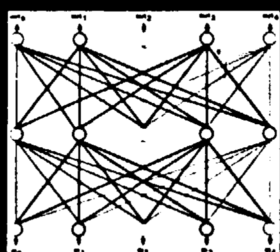
Hopfield



HOPFIELD

J.J. Hopfield demonstrated the formal analogy between a net of neuron-like elements with symmetric connections, called a "Hopfield Net", and a material called a spin-glass, which consists of a random mixture of both ferromagnetically and anti-ferromagnetically interacting spins, exhibiting no net magnetism. Each element of a Hopfield net must both excite and inhibit its neighbors.

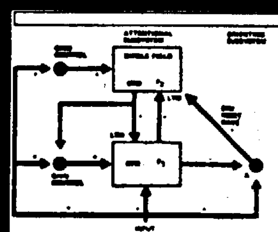
Backward-Error Propagation



RUMMELHART

There are many models in the real world that cannot be represented in a two-layer system such as the Hopfield model. For example, there exist no values that can be assigned to connection strengths to yield to appropriate outputs for the exclusive-or (XOR) function. The solution is to introduce a third layer, called the hidden layer, between the input and output layers. This hidden layer creates the ability to incorporate an internal representation that facilitates difficult mappings between the two external layers.

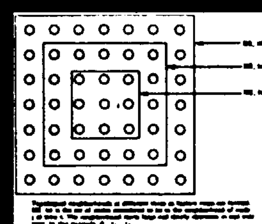
Adaptive Resonance Theory



GROSSBERG

Carpenter and Grossberg, in the development of their Adaptive Resonance Theory, have designed a net which forms clusters and is trained without supervision. The leader algorithm selects the first input as the exemplar in the first cluster. The next input is compared to the first input exemplar. It "follows the leader" and is clustered with the first if the distance of the first is less than a threshold. Otherwise it is the exemplar for the new cluster. This process is repeated for all following inputs.

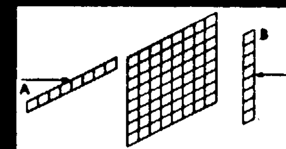
Self-Organizing Maps



KOHONEN

One important organizing principle of sensory pathways in the brain is that the placement of neurons is orderly and often reflects some physical characteristic of the external stimulus being sensed. For example, at each level of the auditory pathway, nerve cells and fibers are arranged anatomically in relation to the frequency which elicits the greatest response in each neuron. Kohonen presents one such algorithm which produces what he calls self-organizing feature maps similar to those that occur in the brain.

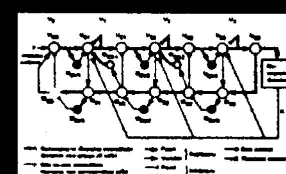
Bidirectional Associative Memory



KOSKO

A bidirectional associative memory (BAM) is a two-layer nonlinear feedback network that behaves as a heteroassociative content addressable memory. M stimulus-response associations (A_i, B_i) are stored by a BAM by summing bipolar correlation matrices. They are recalled as fixed points of the BAM dynamical system.

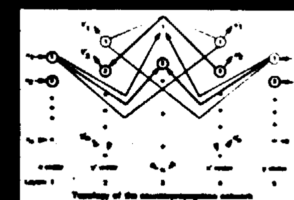
Neocognitron



FUKUSHIMA

The model is a hierarchical multilayered network consisting of a cascade of many layers of simplified neural cells. It has backward as well as forward connections between cells in adjoining layers. The forward signal manages the function of pattern recognition, while the backward signal manages the function of selective attention and associative recall. The forward and backward signals interact with each other at every stage of the hierarchical network.

Counter Propagation



HECHT-NIELSEN

The counterpropagation network (CPN) will self-organize a near-optimal lookup table approximation to the mapping used to generate its data. The method works equally well for both binary and continuous vector mappings. It is shown that for a sufficiently large network the mapping approximation can be made essentially as accurate as desired. The counterpropagation network architecture is a combination of a portion of the self-organizing map of Kohonen and the outstar structure of Grossberg.

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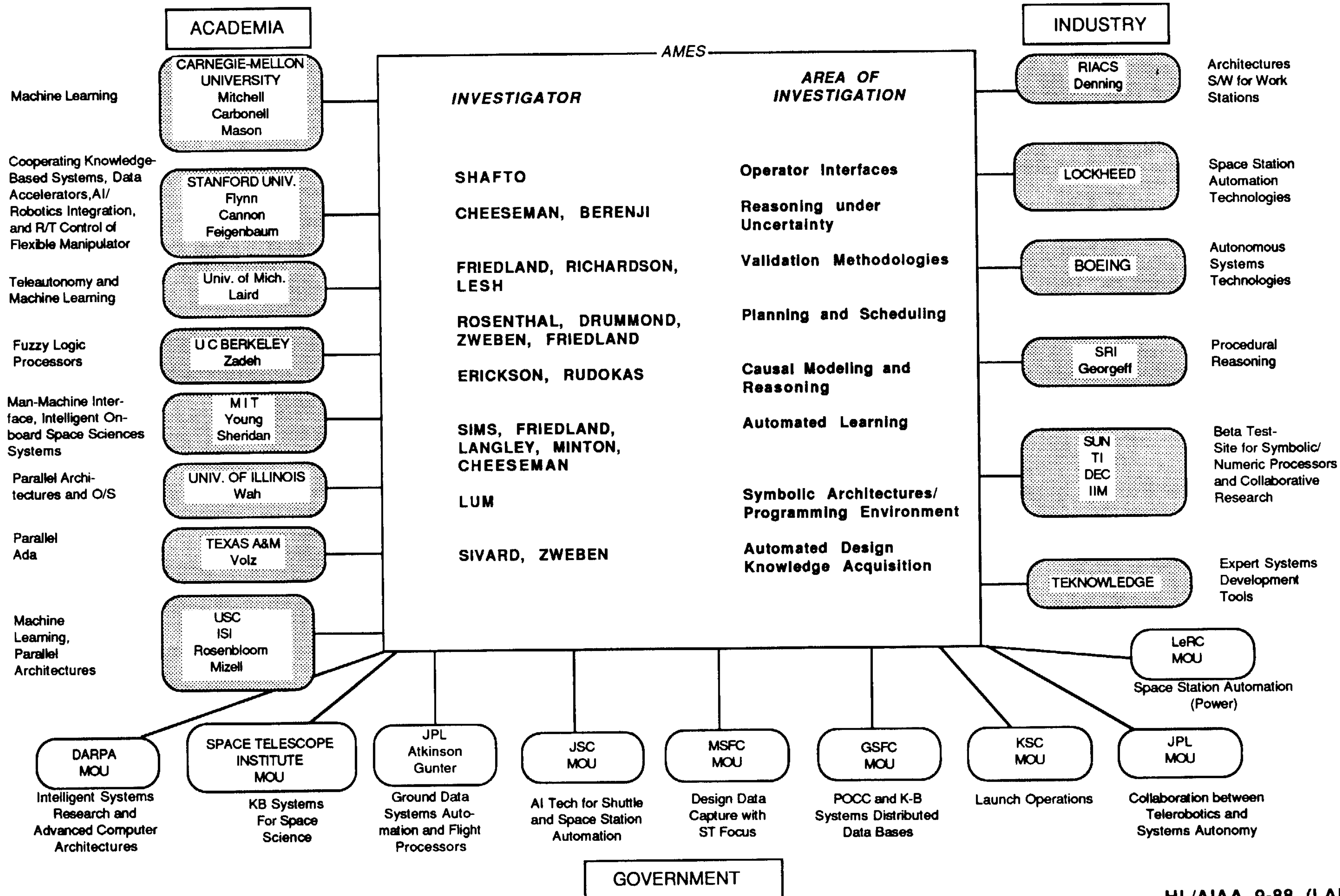

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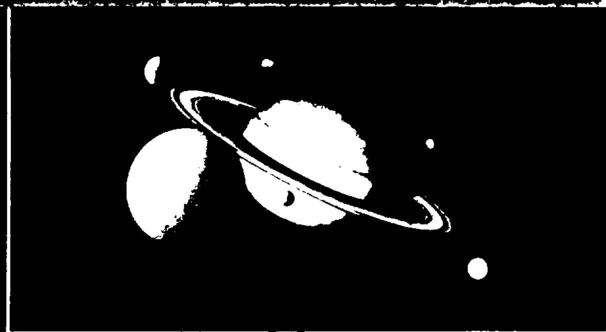
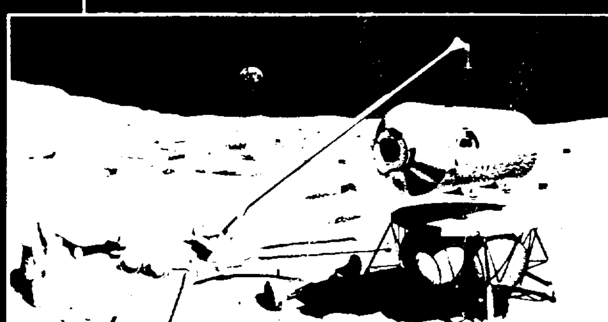
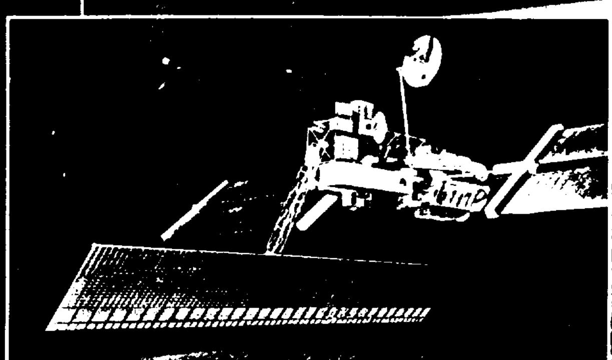


America's Future in Space





C-4